Claremont McKenna College

Defund the Police? An Exploration of the Relationship Police Budget and Officer-Involved Killings

Submitted to
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Abstract

This study aims to examine the relationship between police budget and killings by police. Using a panel data set of police budgets and police killings between 2013 and 2019, I estimate fixed effects models to explore the relationship of interest and use a Poisson conditional fixed effects model to examine the robustness of my results. For a given city-year, I find a statistically significant negative association between the proportion of city resources devoted to police resources and killings per 10,000 arrests, and between the Police Budget Per-Capita and killings per 10,000 arrests. I also find, for a given city-year, that the presence of an indicator variable proxying for the presence of an officer-worn body camera program is associated with additional Killings per 10,000 Arrests, and that this estimate is statistically different from zero.

Keywords: Police violence, police killings, police budget, officer-worn body cameras

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1. Introduction

The murder of George Floyd in May 2020 by Minneapolis Police Officer Derek Chauvin sparked international protest and widespread re-evaluation of the way policing is conducted in American cities (Wamsley, 2021). For the first time, the rallying cry to "Defund the Police" received mainstream attention as a solution to the problem of officer use of lethal force (King, 2020). Proponents of defunding argue that resources cause more use of lethal force, while proponents of increasing funding reason that this funding can be invested in less-lethal methods of intervention like de-escalation training and accountability tools like body cameras.

However, scholarly investigation of the relationship between funding and police violence is limited in the current literature. Most academic research on police violence has focused on the prevalence and demographic distribution of deadly use of force, and on the efficacy of non-lethal interventions. This study attempts to fill this gap by examining the relationship between police killings and funding in 56 American cities between 2013 and 2019.

I put together a panel data set of police killings and police budgets for this eight-year period and estimate fixed effects models to explore the relationship of interest. For a given city-year, I find a statistically significant negative association between the proportion of city resources devoted to police resources and killings per 10,000 arrests. Furthermore, I find a statistically significant negative association between the Police Budget Per-Capita and killings per 10,000 arrests. I also find, for a given city-year, that the presence of an indicator variable proxying for the presence of an officer-worn body camera program is associated with additional Killings per 10,000 Arrests, and that this estimate is statistically different from zero.

2. Literature Review

While ample research has been conducted on deadly use of force by police and the efficacy of non-lethal interventions, investigations of the specific relationship between funding and police violence are limited. There is some research to suggest that financial investment in policing can produce desirable results for the community. Evans & Owens (2006) find that police added to their departments by the Community Oriented Policing Services (COPS) program generated "statistically significant reductions in auto thefts, burglaries, robberies, and aggravated assaults." However, broader research on the relationship between budget and Still, understanding the body of literature on deadly use of force by police and the efficacy of non-lethal interventions is instrumental in exploring the effect of the proportion of a city's budget devoted to police resources and these departments' use of deadly force. The existing literature on deadly use of force, nonlethal strategies, and police funding is reviewed in this section.

I. Deadly Use of Force

Law enforcement agencies have increasingly garnered public scrutiny for high-profile deadly uses of force on civilians in recent years (BBC, 2021). In reality, incidents where police use or threaten force are relatively rare–Hickman et al. (2009) estimates that this occurs in 1.7% of all contacts and in 20.0% of all arrests–but the dire consequences of choosing to employ deadly force necessitate careful investigation.

A significant amount of research has examined situational factors that might influence use of force, including race of the citizen, race of the officer, and relative authority between citizen and officer. Tobit analyses conducted by Jacobs and O'Brien (1998) indicated that racial minorities experience greater risk of police killings. More recently, the Nix et al (2017) examination of 990 fatal police shootings, evaluating possible implicit bias, finds ied that white civilians were significantly more likely than minority civilians to have been attacking at the time of the shooting, and that Black civilians were more than twice as likely as white civilians to have been unarmed at the time of the shooting. Alpert et al. (2004) established support for a relationship between level of force and officer race and found that police interactions with civilians were more likely to include greater force when the civilian appears to behave with less authority than the officer.

Incidents of lethal force do not appear to be increasing over time in the United States–using incident-level national data, Shane et al (2017) found that fatalities were stable across 2015-2016, and established for the first time state-level base rates for fatal police shootings.

More recently, independent organizations, such as Mapping Police Violence (2021) have aggregated nationwide statistics on incidents of lethal force, which may be leveraged to explore the dynamics of lethal use of force in greater depth.

II. Efficacy of Non-Lethal Interventions

The tragic nature of lethal force–justified or unjustified–is largely undisputed, but there is no consensus on how this should impact funding. This section discusses the efficacy of less-lethal methods of police intervention.

a. De-Escalation Training

In response to contentious use of force incidents, de-escalation training has been implemented in law enforcement agencies across the U.S. in recent decades. Preliminary studies have shown encouraging results, but further testing is required before a consensus can be reached. Engel et al's (2020) evaluation of 64 de-escalation programs found that de-escalation training led to "slight-to-moderate" improvements at the individual and organizational level with few unfavorable consequences.

More recently, Goh’s (2021) case study of the effect of de-escalation training on use of force incidents a in a high-crime and high-poverty New Jersey city revealed that while de-escalation training had no significant impact on use of serious force for individual officers, a department-wide synthetic control analysis de-escalation training led to a 40% reduction in incidents involving use of serious force. Goh concludes that de-escalation training has greater potential to reduce police use of force than other recently proposed measures, but cautions against extrapolation of this case-study to different environments.

b. Body-Worn Cameras

Use of body-worn cameras by law enforcement agencies has expanded quickly over the decade. Evidence suggests that these cameras are an effective tool for ensuring accountability on the part of law enforcement officers and reducing violence, corruption, and discrimination in the U.S. judicial system.

In the world's first randomized controlled trial of police body-worn cameras, Ariel et al (2014) empirically tested the use of body-worn-cameras in a randomized control setting to determine their effect on both use of force and complaints against police. Results indicated that the likelihood of force being used in experimental conditions was approximately half that in the control setting. Similarly, the number of complaints filed against law enforcement officers was ten times lower in experimental conditions than in the control setting. Furthermore, the dollar benefit-to-cost ratio of employing this technology was estimated to be roughly 4:1, indicating that this is a reasonable expenditure.

A follow-up study conducted by Sutherland et al (2017) revealed that the lower rates of both use of force and complaints against police described by Ariel et al were sustained during the following years. This indicates that officers do not respond to the presence of the cameras and that the effects of the cameras on use of force and complaints against police may be enduring. In other words, this case study provides strong evidence of the long-term efficacy of body cameras in reducing serious use of force in civilian-officer interactions.

A number of other case studies have been conducted that found similar results when evaluating the efficacy of body-worn cameras. Shane et al, discussed above, found similar results: the mean rate of fatalities was higher for officers not wearing a body camera when compared with those who did wear one. Jennings et al (2015) sought to evaluate the effect of police-worn body cameras on officers' response to resistance and external officer complaints in a randomized control trial of Orlando Police Department officers. The results indicate that the prevalence of negative response to resistance incidents and the frequency of serious external complaints were significantly lower for officers randomly assigned to wear body cameras than for officers from the control group.

III. Potential Militarization of Police

On the other hand, proponents of decreasing police funding worry that additional funding could facilitate increased militarization of police forces, which have few benefits and have been shown to increase with use of deadly force. As noted by Mummolo (2018), militarized SWAT teams provide no identifiable benefits when considering violent crime reduction and officer safety, and are disproportionately deployed in minority communities. More concerning are the results of Delehanty et al (2017) and Kosliki et al (2021), which explore the relationship between police deadly force and the 1033 program, which transfers military surplus equipment to law enforcement agencies. Delehanty et al found a positive and statistically significant relationship between 1033 transfers and fatalities from officer-involved shootings at the county level from four states. Kosliki et al examined 2973 agencies nationwide and found a moderate, positive relationship between the number of 1033 Program items obtained and fatal force.

However, other research indicates less-alarming results of the 1033 Program. Harris et al (2014) investigate the effects of a department receiving tactical tools and weapons on citizen complaints, assaults on police officers, and offender deaths, finding that that these items generally have a positive impact. Among the most notable effects are "notably educed citizen complaints, reduced assaults on officers, increased drug crime arrests, and no increases in offender deaths (Harris et al, 2014)."

IV. Police Budget Trends

According to the Bureau of Justice Statistics, state and local police budgets have steadily increased on average over the last two decades (Bureau of Justice Statistics, 2020). Literature linking police budgets with other trends is limited, but not altogether absent. Zhao et al (2010) examined the local political culture, the nature of socioeconomic conditions, and the prevalence of incremental budget decision-making processes as the determinants of police budget allocation from municipal budgets and found that most of the variation in share of allocation to police agencies was explained by the incremental budgeting aspect of annual budgeting in municipal governments.

3. Data

I. Data Sources

For my empirical analysis of the relationship between funding for city policy budgets and police killings, I combine data from two sources: Mapping Police Violence's Police Killings Database and a hand-collected novel dataset of city-level police budget information.

a. Police Killings Dataset

Data on police killings were retrieved from Mapping Police Violence's Database (Referred to hereafter as the Police Killings Dataset), which includes 9,038 observations between 2013 and 2021. The information in this database was aggregated from three large, comprehensive, databases: FatalEncounters.org, the U.S. Police Shootings Database and KilledbyPolice.net into a list of individual killing victims (About the Data, 2021). MPV independently collected additional data from social media, obituaries, criminal records databases, police reports and other sources to contribute additional demographic information to its database (About the Data, 2021). Variables will be defined more specifically in the Final Dataset section.

The database also aggregates killings by Police Department for the 101 relevant American cities. This alternative aggregate set includes the sum of all killings between 2013 and 2021 with breakdowns by race and whether the killing was recorded by an officer-worn body camera. Also included are a count of the violent crimes and a count of the total arrests for each city for each year from 2013 to 2019, as well as the total population (Census ACS 5 Year 2018) for each city (About the Data, 2021).

This study utilizes the following information from the MPV database: date and location of the incident, race of the deceased, whether or not the killing was recorded by an officer-worn body camera, the violent crime count and the total arrest count for each city-year, the Census

ACS 5 Year 2018 population for each city. These data were either incorporated into my regression models outright or transformed into the appropriate variables as outlined in the Finalized Dataset section.

b. Budget Dataset

A dataset containing the relevant budget information for selected cities was not readily available, so I hand-collected a novel dataset for the purposes of this study. I perused the website of the financial department of each city listed in the MVP dataset and used city budget books to collect budget measures of interest. I attempted to use the full adopted city budget books wherever available, but many cities did not include this version of the budget. Examples of alternative documents I used to obtain yearly budget measures include the proposed budget for each year, the city council's recommended budget, and various budgets-in-brief. Additionally, since city budget documents are not standardized, there was considerable variation in how budgets were presented. This was particularly challenging when budgets were not aggregated by departmental allocation. In collecting the budget measures, I prioritized consistency of measures across time within a city, even if the data reflect some minor differences across cities.

The budget measures of interest are the Total City Budget in Dollars and the Police Department Budget in Dollars. Where available, the All Funds Grand Total figures were used for Total City Budget. Where All Funds Grand Total figures were not available, General Fund Grand Total figures were used instead. Corresponding figures were used for the Police Department budgets: For cities where All Funds Grand Total figures were available, full Police Departmental budgets were used and for cities where only General Fund Grand Total figures were used, the portion in dollars of the police budget that came from the General Fund was used.

Rarely did these figures differ significantly–for most cities, the police budget came primarily or exclusively from the general fund.

c. Finalized Dataset

Data from the Police Killings Dataset and the Budget Dataset were combined in a panel dataset of 51 cities by city-year between 2013 and 2019 including the following variables:

- Year: Fiscal years assigned to calendar years. Retrieved from the Police Killings Dataset.
- Killings: The number of killings of people by police per calendar year, where a killing is defined as "A case where a person dies as a result of being shot, beaten, restrained, intentionally hit by a police vehicle, pepper sprayed, tasered, or otherwise harmed by police officers, whether on-duty or off-duty" (About the Data, 2021). Retrieved from the Police Killings Dataset.
- City Budget: Measured in USD, retrieved directly from the Budget Dataset
- Police Budget: Measured in USD, retrieved directly from the Budget Dataset
- Budget Ratio: The ratio of the Police Budget to the City Budget for each city-year
- Crime Rate: Calculated as the number of violent crimes per city-year divided by the city population, both from the Police Killings Dataset.
- Body Cam: A binary variable that indicates whether at least one killing by a given police department in a given year was witnessed by an officer-worn body camera, based on the Police Killings Dataset. Used as a proxy for whether or not a police department has a body camera program in a given year.
- Killings per 10,000 Arrests: Count of killings per city-year divided by the count of arrests per city-year times 10,000.

- Percent Black: The annual Black population of each city as a proportion of the Census ACS 5 Year 2018 population, both retrieved from the Police Killings Dataset.
- Arrest Count: A count of arrests for each city-year, retrieved from the Police Killings Dataset.
- Violent Crime Count: A count of violent crimes reported for each city-year, retrieved from the Police Killings Dataset.

II. Summary Statistics

Table 1 presents summary statistics across all city-years for the variables of interest–in particular, those used in the regressions and those used to compute the variables used in the regressions. The high standard deviations for most of these variables indicates a large degree of variation within the data. Therefore, it will be helpful to investigate select variables on their own over time. In particular, I will examine the variables that measure budget and killings.

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Killings	2.595982	3.231512	0	23
City Budget (USD)	1620000000	210000000	86000000	17800000
Police Budget (USD)	222000000	288000000	33200000	1780000000
Budget Ratio	.192788	.1267217	.0522945	.6444833
Crime Rate	11.24335	14.70446	.287926	77.73237
Body Cam	.2008929	.401116	0	1
Killings per 10,000 Arrests	1.510522	1.490368	0	8.316008
Percent Black	.1919492	.1631461	0093404	.6396392
Arrest Count	19278.95	17060.67	2064	112862
Violent Crime Count	4412.586	5770.943	207778	3959657
Police Budget Per-Capita	336.5074	139.7574	118.1695	1457.574

Table 1. Summary Statistics for Variables of Interest Across City-Years

a. Variation in Budget Over Time

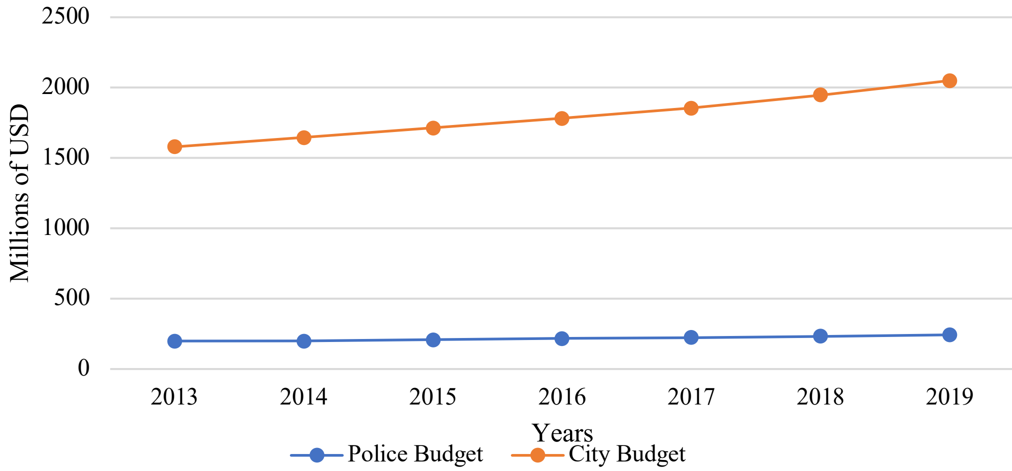

Figure 1. Average City and Police Budget for all cities, 2013-2019.

As shown in Figure 1, the average Police Budget has strictly increased over time, with few exceptions even amongst individual cities. However, this growth has been notably outpaced by increases in the average City Budget, which has increased nearly nine times as quickly. Therefore, it should come as no surprise to see the budget ratio decrease.

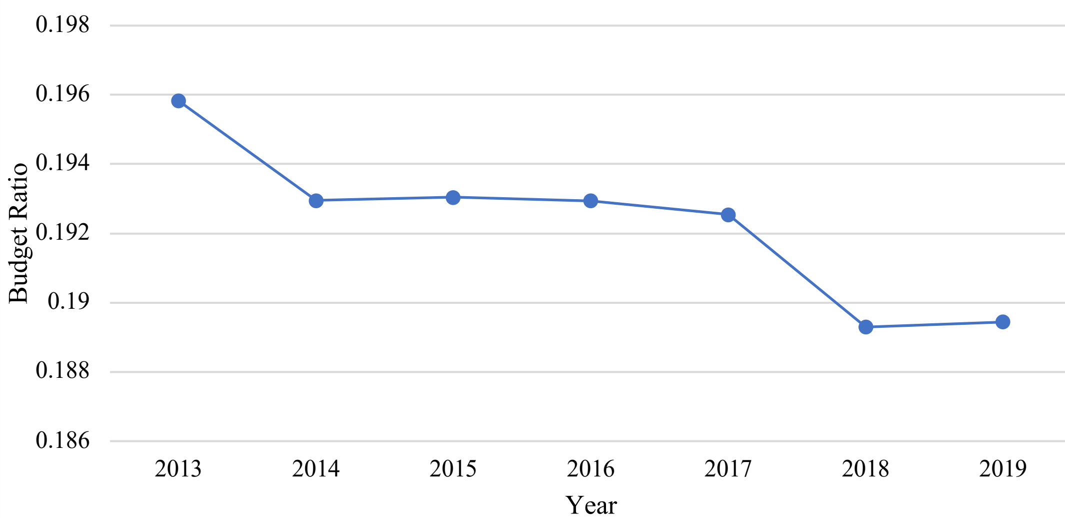

Figure 2. Average budget ratio of all cities, 2013-2019

Figure 2 shows that budget ratio has decreased on average between 2013 and 2019. Fort Worth, Tucson, and Scottsdale had the largest budget ratios, all averaging above 0.5. Fort Worth saw some fluctuation, Tucson trended upwards, and Scottsdale trended downwards. Denver, Seattle, St. Paul, Raleigh, and Chesapeake had the lowest budget ratios, averaging below 0.07. Denver and Raleigh trended down over time while Seattle trended up. St. Paul trended up negligibly, while Chesapeake trended up negligibly.

b. Variation in Killings Over Time

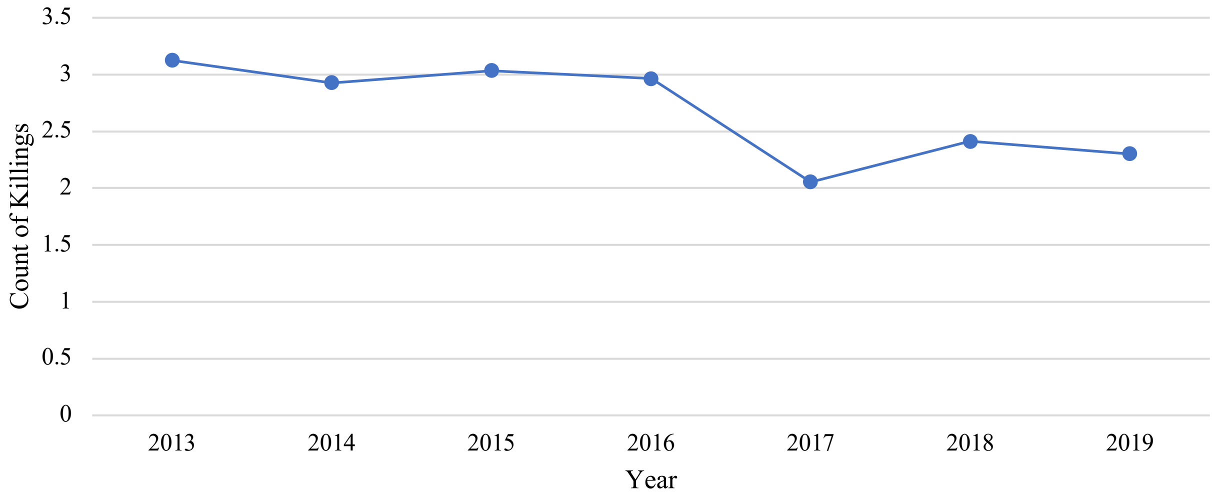

Figure 3. Average count of killings for all cities, 2013-2019

Figure 3 shows that, on average for all cities, the count of killings has decreased between 2013 and 2019. Cities with a lower count of killings do not appear to reliably trend up or down over time-in killings per year appear to change sporadically. Cities with the largest count of killings, Los Angeles, Chicago, and Houston, appear to trend towards fewer killings over time. Los Angeles and Chicago saw more dramatic decreases, while Houston's appears more modest.

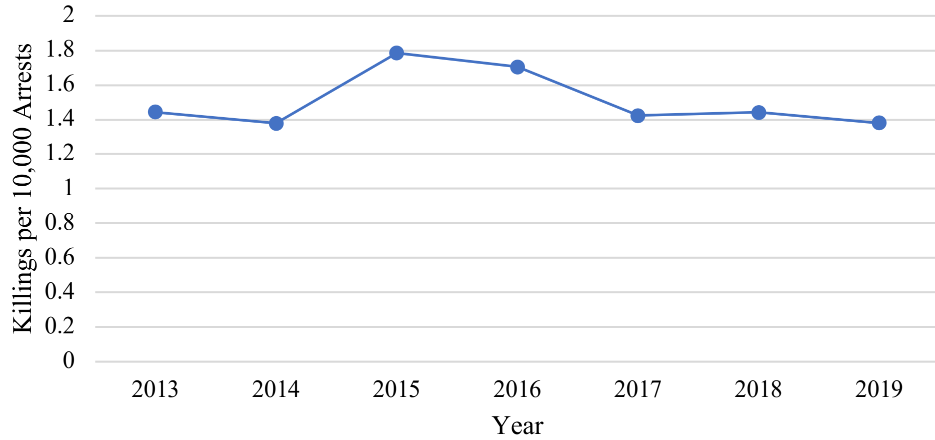

Figure 4. Average Killings per 10,000 Arrests for all cities, 2013-2019

Figure 4 reveals that the average Killings per 10,000 Arrests for all cities, by contrast, has remained more steady. While there was some fluctuation between 2013 and 2019, at a jump up to high of nearly 1.8 in 2016, the average began and ended in nearly the same pattern: a decrease of 0.0645 between 2013 and 2014, and a decrease of 0.0594 between 2018 and 2019.

4. Empirical Strategy & Results

I. Models

a. Fixed-Effects Model

I estimate fixed-effects models using the following specification:

$$Y_{it} = \alpha + \beta X_{it} + \psi_i + \gamma_t + \varepsilon_{it}$$

where Y_{it} is a measure of killings per 10,000 arrests per city-year, X_{it} is a vector of city-year characteristics, ψ_i represents city fixed effects and γ_t represents year fixed-effects, i denotes individual city, t denotes time, and ε is an error term with the usual properties.

In this model, city fixed effects are controlling for time-invariant factors that explain variation in police cities across cities, and year fixed effects are controlling for national time-varying shocks that explain variation in police killings over time.

b. Conditional Fixed-Effects Poisson Model

I estimate conditional fixed-effects Poisson models using the following specification:

$$Z_{it} = \alpha + \beta X_{it} + \psi_i + \gamma_t + \varepsilon_{it}$$

where Z_{it} is count of killings per city-year, X_{it} is a vector of city-year characteristics, ψ_i represents city fixed effects and γ_t represents year fixed-effects, i denotes individual city, t denotes time, and ε is an error term with the usual properties.

II. <u>Results</u>

Two measures of police budget are examined in the following regressions: Budget Ratio, which measures the proportion of a city's budget devoted to police resources, and Police Budget Per-Capita. Since the Annual Crime Rate was only obtainable for the years 2013-2019, the number of observations drops from 448 to 355. The first set of regressions utilized the fixed effects model.

When Killings per 10,000 Arrests is regressed onto Budget Ratio with controls for Annual Crime Rate and an indicator variable proxying for the presence of a Body Camera Program, the results summarized in Table 2 were obtained.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Budget Ratio	-3.138539	1.741097	-1.80	0.077	-6.627775	.3506966
Crime Rate	-.0277546	.021431	-1.30	0.201	-.0707032	.015194
Body Cam	.7722249	.2246896	3.44	0.001	.321937	1.222513

Table 2. Fixed-Effects Regression of Killings Per 10,000 Arrests onto Budget Ratio, Crime Rate, and Body Cam

A one standard deviation (0.13) increase in Budget Ratio is associated with a decrease of 0.4 Killings per 10,000 Arrests. This relationship is statistically significant at the 10% significance level, so we can reject the null hypothesis. This is nearly a quarter of the average number of Killings per 10,000 Arrests (1.510522).

Each percentage point increase in annual crime rate is associated with 0.028 fewer killings per 10,000 arrests. This relationship is not statistically significant, so we fail to reject the null hypothesis.

The Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, is associated with 0.77 more Killings per 10,000 arrests. This relationship is statistically different from 0 at the 0.1% significance level, so we can reject the null hypothesis.

When Killings per 10,000 Arrests is regressed onto Police Budget Per-Capita with controls for Annual Crime Rate and an indicator variable proxying for the presence of a Body Camera Program, the results in Table 3 were obtained. The directionality of each relationship was consistent with the first regression.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Police Budget Per-Capita	-0.0006641	0.0002748	-2.42	0.019	-0.0012149	-0.0001133
Crime Rate	-0.0273122	0.0213557	-1.28	0.206	-0.0701099	0.0154856
Body Cam	0.7724753	0.2240927	3.45	0.001	0.3233836	1.221567

Table 3. Fixed-Effects Regression of Killings Per 10,000 Arrests onto Police Budget Per-Capita, Crime Rate, and Body Cam

A $100 increase in Police Budget Per-Capita is associated with a 0.066 decrease in Killings per 10,000 arrests. This relationship is statistically significant at the 5% significance level, so we can reject the null hypothesis.

Each percentage point increase in annual crime rate is associated with 0.027 fewer killings per 10,000 arrests. However, this relationship is not statistically significant, so we fail to reject the null hypothesis.

The Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, is associated with 0.77 more Killings per 10,000 arrests when compared with no Body Camera program. This relationship is statistically significant at the 0.1% significance level, so we reject the null hypothesis.

To explore the robustness of my results, I estimate a second model using the number of killings as the outcome variable. Because this variable is a count, I employ a Poisson regression. Results are reported in Tables 4 and 5.

Killings	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Budget Ratio	-4.244864	2.985286	-1.42	0.155	-10.09592	1.606189
Violent Crime Count	-0.0000134	0.0000133	-1.01	0.314	-0.0000395	0.0000127
Arrest Count	$3.83 \cdot 10^{-6}$	$4.32 \cdot 10^{-6}$	0.89	0.376	$-4.64 \cdot 10^{-6}$	0.0000123
Body Cam	0.2758518	0.1097731	2.51	0.012	0.0607004	0.4910032

Table 4. Poisson Conditional Fixed-Effects Regression Killings of onto Budget Ratio, Violent Crime Count, Arrest Count, and Body Cam

The results from the Poisson model regressing Killings on Budget Ratio, Violent Crime Count, Arrest Count, and Body Camera Indicator, shown in Table 4 were consistent in direction with the results obtained from the fixed effect model: The relationships between Budget Ratio and Killings and between Violent Crime Count and Killings are both negative. The relationship between the Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, and Killings was positive. The relationship between Arrest Count and Killings was also positive, but only just.

Killings	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Police Budget Per-Capita	-0.0007485	0.0013244	-0.57	0.572	-0.0033444	0.0018474
Violent Crime Count	-0.0000104	0.0000125	-0.84	0.404	-0.0000349	0.000014
Arrest Count	$3.97 \cdot 10^{-6}$	$4.24 \cdot 10^{-6}$	0.94	0.348	$-4.33 \cdot 10^{-6}$	0.0000123
Body Cam	0.282115	0.1098225	2.57	0.010	0.0668668	0.4973631

Table 5. Poisson Conditional Fixed-Effects Regression of Killings onto Police Budget Per-Capita, Violent Crime Count, Arrest Count, and Body Cam

The results were similarly consistent for the Poisson model regressing Killings on Police Budget Per-Capita, Violent Crime Count, Arrest Count, and Body Camera Indicator, shown in

Table 4. The relationships between Police Budget Per-Capita and Killings and between Violent Crime Count and Killings are both negative. The relationship between the Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, and Killings was positive. The relationship between Arrest Count and Killings was also very slightly positive.

I also estimated the fixed-effects models separately for cities above and below the median Percent Black (0.138) in order to investigate how these variables trended in areas with lower and higher Black populations. The first subset of regressions was estimated for cities with a Black population percentage above the median for all cities: one regression using the budget ratio and another using the per capita police budget. A second subset of regressions was estimated for cities with a Black population percentage above the median for all cities: one regression using the budget ratio and another using the per capita police budget. Note that the sample size for the regressions therefore falls in half.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Budget Ratio	-2.187972	1.552236	-1.41	0.170	-5.372896	0.9969533
Crime Rate	-0.0413957	0.0405548	-1.02	0.316	-0.1246073	0.0418159
Body Cam	0.6094219	0.3184312	1.91	0.066	-.0439448	1.262789

Table 6. Fixed-Effects Regression of Killings per 10,000 Arrests for cities above the median Percent Black onto Budget Ratio, Violent Crime Count, Arrest Count, and Body Cam

When Killings per 10,000 Arrests is regressed onto Budget Ratio with controls for Annual Crime Rate and Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, for cities with a Black population percentage above the median Percent Black, for all cities, the results in Table 6 were obtained.

A one standard deviation (0.131) increase in Budget Ratio is associated with a decrease of 0.412 Killings per 10,000 Arrests. Each percentage point increase in annual crime rate is associated with 0.0414 fewer killings per 10,000 arrests. However, neither relationship is statistically significant, so we fail to reject the null hypothesis.

The Body Camera indicator is associated with 0.609 more Killings per 10,000 arrests. This relationship is statistically different from zero at the 10% significance level, so we can reject the null hypothesis.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Budget Ratio	-5.333511	4.408506	-1.21	0.237	-14.37902	3.711996
Crime Rate	-0.0229474	0.0243598	-0.94	0.355	-0.0729295	0.0270348
Body Cam	1.015747	0.3421556	2.97	0.006	0.3137021	1.717793

Table 7. Fixed-Effects Regression of Killings per 10,000 Arrests for cities below the median Percent Black onto Budget Ratio, Violent Crime Count, Arrest Count, and Body Cam

When Killings per 10,000 Arrests is regressed onto Budget Ratio with controls for Annual Crime Rate and Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, for cities with Black population percentage below the median for all cities, the results in Table 7 were obtained.

A one standard deviation (0.127) increase in Budget Ratio is associated with a decrease of 0.676 Killings per 10,000 Arrests. When compared with the regression of cities above the median Percent Black, this indicates that the strength of this correlation is stronger in areas with a lower Black population. Each percentage point increase in annual crime rate is associated with 0.0229 fewer killings per 10,000 arrests. However, neither relationship is statistically significant, so we fail to reject the null hypothesis.

The Body Camera indicator is associated with 1.02 more Killings per 10,000 arrests. This is just under twice the number of killings associated with the presence of a body program than for cities with a Black population percentage above the median. This estimate is statistically different from zero at the 1% significance level, so we can reject the null hypothesis.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Police Budget Per-Capita	-0.0005106	0.0002565	-1.99	0.057	-0.0010369	0.0000156
Crime Rate	-0.0397666	0.0400022	-0.99	0.329	-0.1218443	0.0423111
Body Cam	0.6140262	0.3170436	1.94	0.063	-0.0364934	1.264546

Table 8. Fixed-Effects Regression of Killings per 10,000 Arrests for cities above the median Percent Black onto Police Budget Per-Capita, Violent Crime Count, Arrest Count, and Body Cam

When Killings per 10,000 Arrests is regressed onto Police Budget per Capita with controls for Annual Crime Rate and Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, for cities with Black population percentage above the median for all cities, the above results were obtained.

A $100 increase in Police Budget Per Capita is associated with a 0.0511 unit decrease in Killings per 10,000 arrests. Each percentage point increase in annual crime rate is associated with 0.0398 fewer killings per 10,000 arrests. However, neither relationship is statistically significant, so we fail to reject the null hypothesis for these variables.

The Body Camera indicator is associated with 0.614 more Killings per 10,000 arrests when compared with no Body Camera program. This relationship is statistically different from zero at the 10% significance level, so we reject the null hypothesis.

Killings per 10,000 Arrests	*β*	*Robust Standard Error*	*t*	*P > |t|*	*95% Confidence Interval*	
Police Budget Per-Capita	-0.0017099	0.006172	-0.28	0.784	-0.0143739	0.010954
Crime Rate	-0.0240303	0.0249121	-0.96	0.343	-0.0751458	0.0270851
Body Cam	1.026326	0.3604256	2.85	0.008	0.2867939	1.765858

Table 9. Fixed-Effects Regression of Killings per 10,000 Arrests for cities below the median Percent Black onto Police Budget Per-Capita, Violent Crime Count, Arrest Count, and Body Cam

When Killings per 10,000 Arrests is regressed onto Police Budget per Capita with controls for Annual Crime Rate and Body Camera indicator, used as a proxy for the presence of a Body Camera program in a given city-year, for cities with a Black population percentage below the median for all cities, the above results were obtained.

A $100 increase in Police Budget Per Capita is associated with a 0.171 unit decrease in Killings per 10,000 arrests. This is more than twice the magnitude than that of cities with a Black population percentage above the median for all cities. Each percentage point increase in annual crime rate is associated with 0.0240 fewer killings per 10,000 arrests. However, neither relationship is statistically significant, so we fail to reject the null hypothesis for these variables.

The presence of a Body Camera program in a given city is associated with 1.026 more Killings per 10,000 arrests when compared with no Body Camera program-and again, more than twice the magnitude than that of cities with a Black population percentage above the median for all cities. This relationship is statistically significant at the 1% significance level, so we reject the null hypothesis.

5. Conclusion

I. Discussion of Results & Limitations

This study found statistically significant evidence that an increase in the proportion of a city's budget devoted to police resources is associated with a lower number of Police Killings per 10,000 Arrests. Furthermore, it found statistically significant evidence that an increase in the police budget per capita is associated with a lower number of Police Killings per 10,000 Arrests. It is important to note that these findings do not establish a causal relationship between killings and budget, so the directionality is unclear. While it is possible that increased spending results in fewer killings, the reverse–that funding is increased in response to fewer killings–could also hold true. Furthermore, this association could be explained by other variables not included in the study.

Interestingly, the study also found statistically significant evidence that an indicator variable proxying for the presence of a Body Camera program in a given city-year is associated with increases in the number of Police Killings per 10,000 Arrests across all specifications. Since these findings do not establish a causal relationship between these variables, the direction of causality of this relationship is unclear. The relationship could indicate that the presence of a body camera emboldens officers to engage in risk-taking behavior, but the relationship could just as easily run in reverse: perhaps cities where law enforcement work is dangerous invest in body cameras because they anticipate violent conflict and seek accountability and objectivity. Furthermore, it's possible that this relationship could be explained by a variable that's been omitted from the study.

Lack of data availability was a notable obstacle in this study. Additional cities (up to the 101 included in the Police Killings Dataset) could have been included in the regression if budget information was more readily available. Unfortunately, many cities have not digitized their financial records as far back as 2013, and those that have been digitized are not standardized. Launching inquiries into the financial departments of individual cities is labor-intensive and time-consuming. However, if the timeline of this project were expanded, this outreach might be worthwhile to obtain a more complete dataset.

Furthermore, the list of killings in the MVP Dataset, while more complete than other datasets, is not exhaustive. For example, the 2019 fatal shooting of Miles Hall in Walnut Creek, CA, is nowhere to be found despite ongoing media and legal attention (Mukherchee, 2021).

II. Suggestions for Further Study

As previously suggested, further research into the relationship between the presence of a body camera program and the number of Police Killings per 10,000 Arrests is recommended. While a binary variable accounting for the presence of a body camera program was included in this study, it was not its central focus. Designing a study around this variable and specifically considering the factors that might influence this relationship will likely produce more valuable insights.

The poverty level of poverty and how it is addressed cities may also have a relationship with police killings. Adding variable(s) to account for the poverty level in cities in the dataset would be interesting. Potential variables might include median income or the proportion of the population living below the poverty line. While it may require additional novel data collection, this data should be readily available and this seems to be a reasonable extension of the current study.

The education level of involved officers may have a relationship with police killings. This could include formal education (for example, High School Diploma vs. 4-year degree) or specialized training completed during tenure (for example, de-escalation training). This kind of data would likely be difficult to gather, as police departments tend to be protective of identifying information about officers involved in killings (Friedersdorf, 2014). Standardization of training may differ department-to-department as well, which makes this sort of education difficult to quantify. These obstacles make incorporating these variables difficult. Nevertheless, including them would likely reveal valuable insights.

6. Appendix

I. List of Cities

The following cities are included in the data set.

Arlington
Aurora
Austin
Bakersfield
Baton Rouge
Boston
Buffalo
Chesapeake
Chicago
Chula Vista
Cincinnati
Cleveland
Colorado Springs
Columbus
Corpus Christi
Dallas
Washington
Denver
Durham
El Paso
Fort Wayne
Fort Worth
Fremont
Greensboro
Henderson
Honolulu
Houston
Irvine
Irving
Lincoln
Long Beach
Los Angeles
Louisville
Lubbock

Madison
Memphis
Milwaukee
New Orleans
Norfolk
Omaha
Pittsburgh
Portland
Raleigh
Reno
Rochester
Sacramento
San Antonio
San Diego
Santa Ana
Scottsdale
Seattle
St. Paul
Stockton
Tucson
Tulsa
Virginia Beach

7. References

About the Data. (n.d.). Retrieved May 03, 2021, from https://mappingpoliceviolence.org/aboutthedata

Alpert, G. P., Dunham, R. G., & MacDonald, J. M. (2004). Interactive Police-Citizen Encounters that Result in Force. *Police Quarterly, 7*(4), 475-488. doi:10.1177/1098611103260507

Ariel, B., Farrar, W. A., & Sutherland, A. (2014). The Effect of Police Body-Worn Cameras on Use of Force and Citizens' Complaints Against the Police: A Randomized Controlled Trial. *Journal of Quantitative Criminology, 31*(3), 509-535. doi:10.1007/s10940-014-9236-3

Delehanty, C., Mewhirter, J., Welch, R., & Wilks, J. (2017). Militarization and police violence: The case of the 1033 program. *Research & Politics, 4*(2), 205316801771288. doi:10.1177/2053168017712885

Engel, R. S., McManus, H. D., & Herold, T. D. (2020). Does de-escalation training work? *Criminology & Public Policy, 19*(3), 721-759. doi:10.1111/1745-9133.12467

Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics, 91*(1-2), 181-201. doi:10.1016/j.jpubeco.2006.05.014

Friedersdorf, C. (2014, December 02). How Police Unions and Arbitrators Keep Abusive Cops on the Street. Retrieved May 03, 2021, from https://www.theatlantic.com/politics/archive/2014/12/how-police-unions-keep-abusive-cops-on-the-street/383258/

George Floyd: Timeline of black deaths and protests. (2021, April 22). Retrieved May 03, 2021, from https://www.bbc.com/news/world-us-canada-52905408

Goh, L. S. (2021). Did de-escalation successfully reduce serious use of force in Camden County, New Jersey? A synthetic control analysis of force outcomes. *Criminology & Public Policy*. doi:10.1111/1745-9133.12536

Harris, M. C., Park, J., Bruce, D. J., & Murray, M. N. (2017). Peacekeeping Force: Effects of Providing Tactical Equipment to Local Law Enforcement. *American Economic Journal: Economic Policy, 9*(3), 291-313. doi:10.1257/pol.20150525

HICKMAN, M. J., PIQUERO, A. R., & GARNER, J. H. (2008). TOWARD A NATIONAL ESTIMATE OF POLICE USE OF NONLETHAL FORCE. *Criminology & Public Policy, 7*(4), 563-604. doi:10.1111/j.1745-9133.2008.00528.x

Jacobs, D., & O'Brien, R. M. (1998). The Determinants of Deadly Force: A Structural Analysis of Police Violence. *American Journal of Sociology, 103*(4), 837-862. doi:10.1086/231291

Jennings, W. G., Lynch, M. D., & Fridell, L. A. (2015). Evaluating the impact of police officer body-worn cameras (BWCs) on response-to-resistance and serious external complaints: Evidence from the Orlando police department (OPD) experience utilizing a randomized controlled experiment. *Journal of Criminal Justice, 43*(6), 480-486. doi:10.1016/j.jcrimjus.2015.10.003

King, M. (2020, June 17). How 'Defund the Police' went from moonshot to mainstream. Retrieved May 03, 2021, from https://www.politico.com/news/2020/06/17/defund-police-mainstream-324816

Koslicki, W. M., Willits, D. W., & Brooks, R. (2021). Fatal outcomes of militarization: Re-examining the relationship between the 1033 Program and police deadly force. *Journal of Criminal Justice, 72*, 101781. doi:10.1016/j.jcrimjus.2021.101781

Mapping Police Violence. (n.d.). Retrieved May 03, 2021, from https://mappingpoliceviolence.org/

Mukherjee, S. (2021, April 21). Miles Hall police killing: Contra Costa DA sets release deadline for report. Retrieved May 03, 2021, from https://www.mercurynews.com/2021/04/20/miles-hall-police-killing-contra-costa-da-sets-release-deadline-for-report/

Mummolo, J. (2018). Militarization fails to enhance police safety or reduce crime but may harm police reputation. *Proceedings of the National Academy of Sciences, 115*(37), 9181-9186. doi:10.1073/pnas.1805161115

Nix, J., Campbell, B. A., Byers, E. H., & Alpert, G. P. (2017). A Bird's Eye View of Civilians Killed by Police in 2015. *Criminology & Public Policy, 16*(1), 309-340. doi:10.1111/1745-9133.12269

Scott, K. M., & Buehler, E. (2020, July 13). State and Local Government Expenditures on Police Protection in the U.S., 2000-2017. Retrieved May 03, 2021, from https://www.bjs.gov/index.cfm?iid=6927&ty=pbdetail&utm_content=slgeppus0017

Shane, J. M., Lawton, B., & Swenson, Z. (2017). The prevalence of fatal police shootings by U.S. police, 2015–2016: Patterns and answers from a new data set. *Journal of Criminal Justice, 52*, 101-111. doi:10.1016/j.jcrimjus.2017.05.001

Sutherland, A., Ariel, B., Farrar, W., & De Anda, R. (2017). Post-experimental follow-ups—Fade-out versus persistence effects: The Rialto police body-worn camera experiment four years on. *Journal of Criminal Justice, 53*, 110-116. doi:10.1016/j.jcrimjus.2017.09.008

Wamsley, L. (2021, April 20). Derek Chauvin Found Guilty Of George Floyd's Murder. Retrieved May 03, 2021, from https://www.npr.org/sections/trial-over-killing-of-george-floyd/2021/04/20/987777911/court-says-jury-has-reached-verdict-in-derek-chauvins-murder-trial

Zhao, J., Ren, L., & Lovrich, N. P. (2010, May/June). Budgetary support for police services in U.S. municipalities: Comparing political culture, socioeconomic characteristics and incrementalism as rival explanations for budget share allocation to police. *Journal of Criminal Justice, 38*(3), 266-275. doi:10.1016/j.jcrimjus.2010.03.003